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Fault Diagnosis of Vehicular Electric Power Generation and Storage

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FAULT DIAGNOSIS OF VEHICULAR ELECTRIC POWER GENERATION AND STORAGE

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I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Hithesh S. Uliyar ENTITLED Fault Diagnosis of Vehicular Electric Power Generation and Storage BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science in Engineering.

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ABSTRACT

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Automotive vehicles are becoming increasingly dependent on electric power, and this trend will accelerate. The health of the vehicular electric power generation and storage (EPGS) system is crucial to enhance vehicle safety, fuel economy, and customer satisfaction. In this research, a state-of-health (SOH) monitoring method is developed for automotive EPGS system, focusing on alternator related faults. Parity relations, characterizing the correlation among EPGS system signals under normal operating conditions, are generated using principal/minor component analysis techniques. Based on a design of structured residuals, the faults under consideration, including shorted diodes, belt slippage, and regulator fault, are successfully detected and isolated. The effectiveness of the diagnostic algorithm is illustrated by using Matlab/Simulink based EPGS Simulation model.

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Introduction

1.1 Importance of Fault Diagnosis

The age of modern era is mainly dependent on availability and appropriate function of complex technological processes. This can be illuminated by various instances [10]. Manufacturing systems are made up of different machine tools, robots and transportation system. In order to guarantee efficient and high quality production, all of these components must be fully functional. Power distribution network operation and transportation systems have direct impact on economy and everyday life. Faults occurring in single component have major effects on availability and system performance as a whole. In case of automobiles, strict regulation of protecting environment can be ensured by timely supervision of engine and shutting off in case of fault occurrence.

Generally, the *fault is an undesirable change in the behavior of the system such that the system can no longer serve its purpose* [10]. It can either be an internal event in the system, which ceases power supply, breakage in the information link or an leakage in pipe or an environmental condition wherein the ambient temperature may stop the reactor. It can also be wrong control input given by the human operator which changes the systems operating point.

Therefore in any complex system, the failure in any component will hamper the performance of overall system. Hence in order to avoid production deteriorations or damage to machines and humans, a definite kind of monitoring system is needed. This paves the path for the study dealing with fault detection and diagnosis. Quick fault detection and isolation can be helpful in avoiding abnormal event progression and also minimize the quality and productivity offsets.

Figure 1.1, illustrates the general block diagram of an complex control system. It comprises of programmable controller (PC), input interfaces, output interfaces, human machine interface (HMI), communication interface, sensors, actuators and controlled process. Closed-loop monitoring information in the control system forms the base for quantitative and qualitative process model. Later, the detection and isolation of main failures in sensors, actuators, and the controlled process is carried [10].

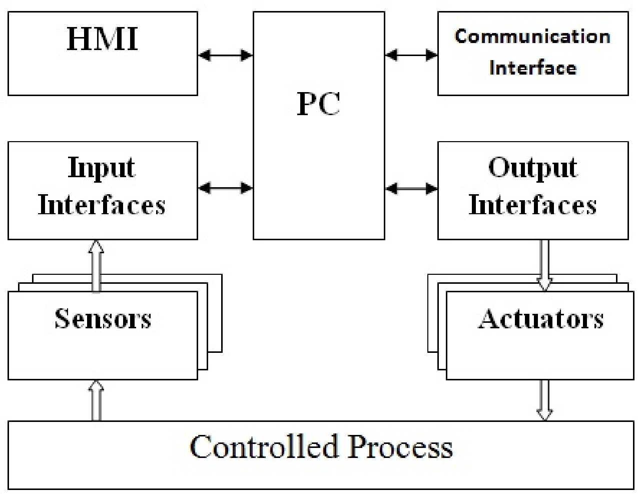

Figure 1.1: General Scheme for Control System [10]

The controller and interfaces in the system are highly reliable and have minimal possibility of malfunctions. On the other side, components such as the sensors, actuators and controlled process are often exposed to intense/harsh field, changes in temperature and humidity, lightning strike and other factors that would easily get the performance of components degraded or damaged. Hence, these components become the main source of failures in process control systems. The faults in general, can be either additive process faults or

Multiplicative faults [13, 15, 7]. Therefore, the major concern would be the diagnosis and accommodation of faults in engineering systems which include production components, appliances, machinery, vehicles etc.

Fault diagnosis is the process of determining the type, size, location of fault based on the observed analytical and heuristic symptoms (i.e. characteristic values obtained from human observation and inspection).

Fault diagnosis can be explained as the process involving following tasks.

- Fault Detection : To make a decision if everything in a system is working fine or something has gone wrong.
- Fault isolation : To determine the exact location or type of the fault that has occurred.
- Fault identification : To estimate the magnitude of the fault occurred.
- Fault accommodation : The task of accommodating the faults in the system by making use of results obtained by fault detection, isolation and identification.

1.2 Fault diagnosis Approaches

Fault diagnosis is often considered as fault detection and isolation (FDI) in the literature [1, 12]. Traditional approach to fault diagnosis is based on hardware redundancy method. This involves multiple sensors, computers, actuators and software to measure and control a particular variable. Generally, the occurrence of fault and its location among system redundant components is decided based on a voting scheme. One of the major drawback of hardware redundancy is additional space requirement due to extra hardware and the second would be high maintenance cost.Two important analytical redundancy approaches for fault detection and diagnosis are model-based approach and model-free approach.

1.2.1 Model-based Approach

Model-based approach mainly makes use of explicit mathematical model of the plant being monitored. One of the most common concept that model based fault diagnosis methods relies on is analytical redundancy. In contrast to physical redundancy [8, 13, 15], the sensor variables are compared with analytically obtained estimation of respective variables. The resulting difference called residuals indicate the presence of faults.

Residual generation is always followed with residual evaluation. Due to the presence of external factors like noise and model errors, the residual is never zero in the absence of faults. Residuals generated have zero mean in the absence of fault. And, it significantly deviates from zero when the fault is present. The generation of residuals can hence be described as the procedure for extracting fault symptoms from the system. The algorithm used to generate residuals are called Residual Generators.

Residual generation methods The residuals can be generated by making use of following approaches [10, 13, 15, 8].

Observer based Methods The basic idea in observer-based methods is to estimate the outputs of system by making use of Luenberger observer in deterministic setting or Kalman filters in stochastic setting. The estimation of state vector is not required for FDI purpose. Instead, the output estimation error is the parameter of interest, as it is required for residual measurement. Any linear process can be represented by following state space form

$$\dot{x}(t) = Ax(t) + bu(t) \tag{1.1}$$

$$y(t) = cx(t). \tag{1.2}$$

Based on the measure of inputs and outputs, the state observer is constructed in order to reconstruct the unmeasurable state variables.

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + He(t) \tag{1.3}$$

$$e(t) = y(t) - C\hat{x}(t) \tag{1.4}$$

where $e(t)$ is output error. Then, the state estimation error is given by

$$\tilde{x}(t) = x(t) - \hat{x}(t) \tag{1.5}$$

$$\dot{\tilde{x}}(t) = [A - HC]\tilde{x}(t) \tag{1.6}$$

The state estimation error tends to zero asymptotically if the observer is stable, and it depends on the design of observer gain H.

In case of multivariable process with disturbances and faults in the plant dynamics and sensor output, the state equations 1.1 and 1.2 can be rewritten as

$$\dot{x}(t) = Ax(t) + Bu(t) + Fv(t) + Lf_l(t) \tag{1.7}$$

$$y(t) = Cx(t) + Nn(t) + Mf_M(t) \tag{1.8}$$

where $v(t)$ represents the disturbance signal, $f_l(t)$ represents fault signals in the plant, $n(t)$ is the disturbance at output, and $f_M(t)$ is the fault signal at output. Therefore, in the presence of fault and disturbance the state estimation error (1.6), becomes

$$\dot{\tilde{x}}(t) = [A - HC]\tilde{x}(t) + Lf_l(t) - HMf_M(t) \tag{1.9}$$

provided the disturbances $v(t) = 0$ and $n(t) = 0$. The output error hence is

$$e(t) = C\tilde{x}(t) + Mf_M(t) \tag{1.10}$$

where $f_l(t)$ and $f_M(t)$ are additive faults. In the presence of faults, the state and the output estimation error $\tilde{x}(t)$ and $e(t)$ deviate from zero and exhibit dynamic behaviors for different $f_l(t)$, $f_M(t)$. Therefore, $e(t)$ can be considered as residual in observer-based fault detection method.

Parity Relations : In this method, the reference model is obtained by identifying plant in fault free situation. Later the model is monitored online. Variations in the online measured parameters from the ones obtained from reference models serve as basis for detection and isolation.

Consider a fixed model G_m running in parallel to the process G_p. the output error can be given by

$$r(s) = [G_p(s) - G_m(s)]u(s) \tag{1.11}$$

If we consider input and output faults (f_u and f_y) and if $G_p = G_m$ then the output error becomes

$$r(s) = G_p(s)f_u(s) + f_y(s) \tag{1.12}$$

equation (1.12) can be used to generate residuals and is called parity equation [13, 15].

The parity equations when formulated for more than one input and output, it would be possible to generate structured residuals so that fault will not influence all residuals, which can be used for fault isolation. Parity equation methods are mainly suitable for detection and isolation of additive faults. They are simpler and easy to implement compared to observer based technique. They have also proved to provide same results as the observer based method [13, 15].

Parameter Estimation The process-model based methods makes use of dynamic process models which are in the form of physics-based mathematical equations. In most of the cases, the process nominal values of parameters are known. And, the actual values of parameters are estimated with parameter estimation technique by making use of input and output signals. Parameter estimation methods operate where model structure is defined (i.e adaptive process models). They are mainly suitable to obtain multiplicative faults. The residual is defined as the deviation between the nominal values of the model parameters and their estimates.

Once the residuals are generated, the next task would be the *Decision making*. This is achieved by examining the residuals obtained for *likelihood faults*. With the help of decision rule, definite kind of fault can be determined. Basically, the decision rule is simple threshold test on the instantaneously generated residual values or comparing the residuals with set of patterns obtained for simple fault or by making use of statistical decision theory [13].

The above discussed techniques of model based approaches to fault diagnosis are powerful if an accurate system model is available. The diagnostic performance may be limited for complex systems where, it is not possible to obtain accurate and robust models.

1.2.2 Model free approach

Data Driven model free approach fulfills the shortcoming of model-based technique for complex process systems discussed above. This approach depends on the availability of large historical data. The data obtained is transformed and presented as *priori* knowledge to diagnostic system. This kind of feature extraction process from process history data is carried to facilitate later diagnosis.

In the literature, The data-driven Fault Detection and isolation (FDI) is said to have undergone three phases in its development. i.e, the signal based FDI, multivariable-statistics-based FDI and Knowledge based FDI.

- Signal-based FDI: This technique mainly makes use of signal processing methods consisting of correlation functions, signal model identification, spectral analysis and signal parity checks [11]. Any unexpected changes occurring in magnitude, phase shift or frequencies of certain signals is considered to be the cause for fault occurrence. In addition to these, the statistical process control(SPC) [11], was applied to monitor abnormal distribution changes of quality data in production lines and hence real time alarms can be produced when the data lies above or below distribution limits.

- Multivariable-statistics-based FDI: Whenever the data is having higher dimensional space, Principal Component Analysis (PCA) can be used to reduce the higher dimensional data to lower dimensional data. The projection axes are called principal components. PCA is been widely used as a standard technique for data analysis and process abnormalities in industrial process [11]. In the fault detection approach, set of PCA components are obtained in the absence of fault in the system. Fault detection is performed by checking for the projection of new data in space spanned by normal/healthy principal components. PCA is widely used to detect faults where large multivariate data sets are produced. dynamic PCA techniques such as moving PCAs and nonlinear PCAs using neural networks have also being used [11].

- Knowledge-based FDI: Knowledge based approach is carried to perform online monitoring for industrial process by making use of continuously accumulated process knowledge. Since the process knowledge is obtained from operational system data, knowledge-based FDI is regarded as data-driven FDD. Knowledge-based FDI makes use of cause effect analysis, expert systems and classification.

1. Fault diagnosis is carried using cause effect analysis by using symbolic graphs or fault analysis trees.
2. Expert systems attempts to mimic the reasoning phase of human experts to carry fault detection and diagnosis.
3. Classification phase makes use of relationship between data and faults to perform required fault diagnosis.

Fuzzy logic and neural networks are used for knowledge based FDI[see, for instance [11] and related references]. Fuzzy logic is used to analyze the residual signals for fault diagnosis, and neural network based FDI, uses available mapping between process variables and faults to determine system faults. Neural networks have also been used to carry residual signal analysis and classify the residual signals into healthy and unhealthy categories [11].

1.3 Research Objectives

In the recent years, automotive vehicles are becoming increasingly dependent on electric power, and this trend will accelerate [6, 21]. This is mainly because of two reasons. First, the number of new electrical components in modern vehicles has been rapidly increasing to satisfy customers' expectation of more performance, safety (e.g., anti-lock braking and stability enhancement system), and comfort (e.g., seat heating, audio and video systems). Second, more and more conventional mechanical or hydraulic components are being replaced by electrical components (e.g., drive-by-wire technologies). As a result of which the health of the vehicular electric power generation and storage (EPGS) system is crucial to ensure reliable power supply to electrical components for enhanced vehicle safety, fuel economy, reliability, and customer satisfaction. Therefore, the development of robust on-board fault detection and isolation (FDI) technology for the EPGS system is becoming increasingly important [18, 21, 28].

Previous works conducted on fault diagnosis of EPGS system, investigated the design of robust state-of-health monitoring algorithms for the battery component[31, 33]. This thesis focuses on another key component of EPGS system, i.e., the alternator. The dynamics of the automotive alternator is very complex. For instance, the field voltage regulator and the diode bridge rectifier in the alternator both have discontinuous switching operations, and the dynamics of the three-phase AC generator is highly nonlinear. Additionally, the limitation of sensor measurements in practical EPGS systems makes the fault diagnosis problem even more difficult. Therefore, statistical data-driven approaches such as principal component analysis (PCA) are more suitable for this research work. Such techniques have also been widely used for fault diagnosis of complex systems, when first principle based methods are not suitable [2, 16, 26].

Based on the above discussions, the research objectives of this thesis include,

1. Study of alternator related faults and thier effects.

2. Develop an EPGS system simulation model for algorithm developement.

3. Develop and validate a fault diagnostic algorithm for EPGS system.

By means of early detection of alternator faults, it helps to warn the driver about alternator faults, and thereby avoid depletion of battery. In addition to this, it also helps the auto manufacturers avoid mistaken replacement of batteries due to alternator faults therby saving warranty cost.

This thesis is organized as follows. Chapter 2 introduces the automotive EPGS system and briefs about its elements and their functions. Chapter 3 explains the EPGS simulation model developed for algorithm evaluation. Also, the fault diagnosis logic developed is explained. Chapter 4 describes the process of data generation and illustrative simulation results. Chapter 5 describes the evaluation results based on real time conditions. Chapter 6 presents the concluding observations and scope for future work.

EPGS system and Fault Effect Analysis

2.1 EPGS SYSTEM

Automobiles are complex system where many sophisticated functions are accomplished. This complex vehicle system can be further split into sub-systems, which paves the path for the study and diagnosis of overall system. EPGS the acronym for vehicular Electric Power Generation and Storage, as the name signifies deals with the study of power generation and storage in vehicle systems. Initially the vehicular electrical system just comprised of the ignition system. The electric starters were introduced in 1912. And by the end of 1930, 6 volt electrical systems were being used. With the increase in engine speed and the need of higher cranking voltage and with the advent of additional on board features like radios, windshield wipers and window regulators, the 6 volt electric system were replaced by present 12 volt electric system.

A typical automotive electrical system is shown in Figure 2.1. Figure 2.2 shows the EPGS system which consists of an alternator, a battery, and two electronic control units (ECUs) including the engine control module (ECM) and body control module (BCM). The EPGS system is expected to supply sufficient electric power to crank the internal combustion engine (ICE) during vehicle starting and to drive numerous electronic components to ensure proper operations of the vehicle

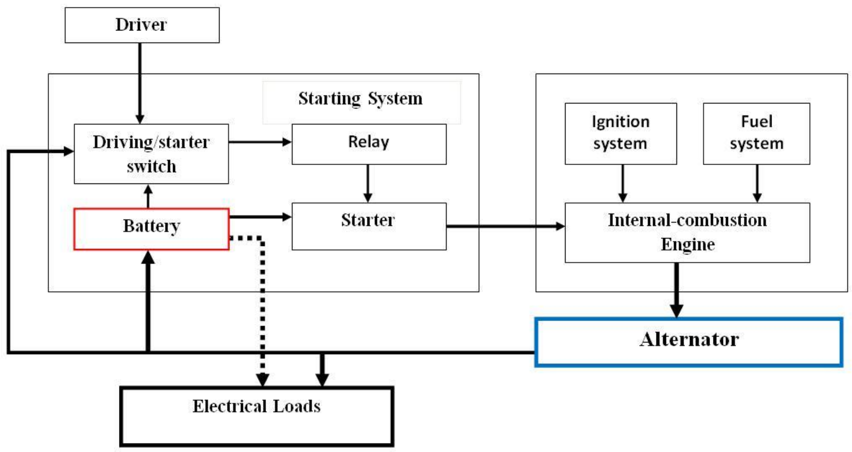

Figure 2.1: Automotive Electrical System [4]

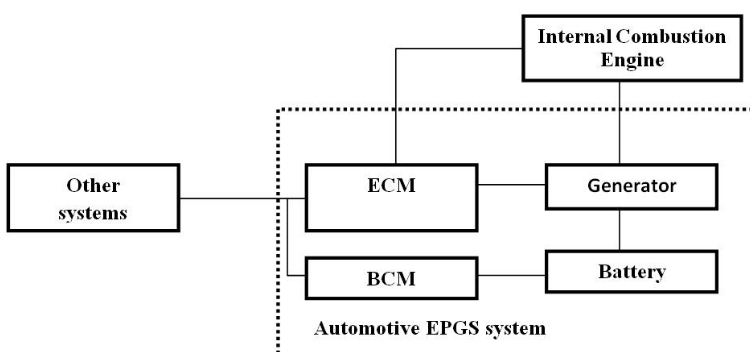

Figure 2.2: Automotive EPGS System [4]

2.1.1 Alternator

Alternator mainly fulfills the electrical power requirement for all electric components. The alternator is composed of a delta stator, a rectifier bridge, a rotor with slip and brushes, a regulator, and a conventional pulley. The internal combustion engine drives the alternator via a drive belt. When the rotor is spun, it creates a rotating magnetic field and induces an AC current into the stator winding. Generally the alternator output depends on the control action of the voltage regulator, which basically responds to the battery terminal voltage and the reference voltage specified by the alternator L-terminal. Battery is the source of storage element.

The alternator mainly works on the principle of electromagnetic induction. The most common design implemented in the alternator is called Claw pole rotor. Normally 12 to 16 poled rotors of this kind are being used. Each end of the rotor interchanges between north and south pole. The stationary loops of wire are called stator and consist of three separate phases. In order to reduce the effect of eddy currents, the windings are mechanically spaced on a laminated core. The three phase windings can be done in two ways - delta and star windings.

The AC signal is converted to DC by the rectifier bridge, which provides voltage to operate the vehicle's electrical system and to charge the battery. Diodes in the rectifier pack also serve to prevent reverse current flow from the battery to the alternator. Figure 2.3 shows the complete rectification circuit along with the voltage regulator.

Excessive charging of lead acid batteries will lead to emission of hydrogen and oxygen from the cells. This is mainly due to the loss of some water of the electrolyte by electrolysis. This process is also called gassing of batteries. In order to prevent the overcharging of batteries in this manner - It is always recommended to charge the battery within 14volts for 12volts battery. This kind of control can be achieved by the voltage regulator. The task of the regulator is mainly to regulate the output voltage to track the reference voltage even if the engine rpm changes. The regulation is mainly attained by changing the duty cycle of the field voltage pwm signal.

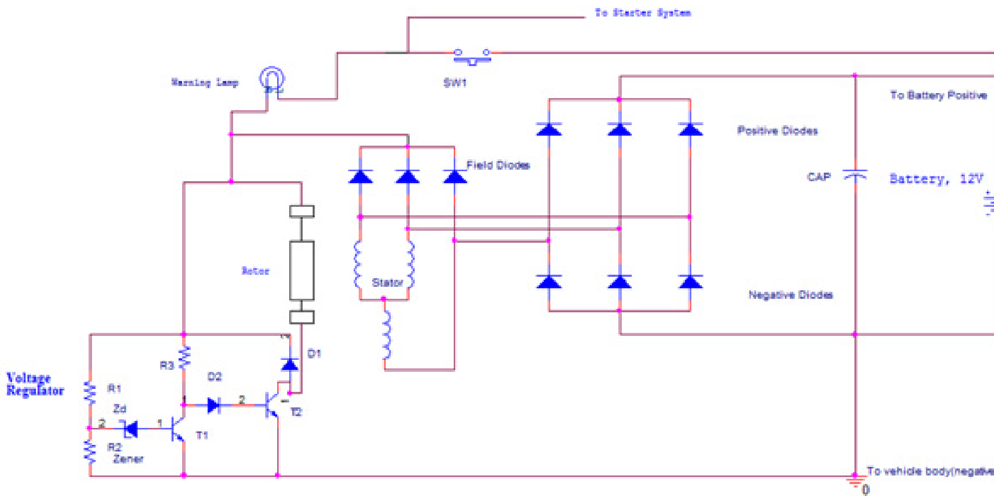

Figure 2.3: Complete Alternator circuit

Figure 2.3 shows the overall alternator model. Initially during the starting phase, the load requirements are fulfilled by the battery. The voltage regulator senses this and it enables the field current to the rotor. During this process the battery voltage starts decreasing. Due to the electromagnetic induction process, the stator provides the increase in output voltage. When the output voltage of around 14.2 volts is obtained the terminals across warning lamp will have same potential, and hence it turns off. This stage of ignition happens in the matter of micro seconds. As the process continues, the voltage regulator removes the current flow to field diodes . Once the Engine is turned on, the battery current is no more used for excitation process by the voltage regulator. Hence the alternator can be termed as self exciting device.

2.1.2 Battery

The second important component of EPGS system would be the Battery. The battery being the additional energy source, supplies electric power to the vehicle under the following situations

- The engine is not operating (for instance, engine cranking, and quiescent loads).
- The energy generated by the alternator cannot meet the demands of the load (for instance, when the ICE is idle with large current consuming devices being switched on or the alternator is defective).
- The battery stabilizes the system voltage in the presence of sudden electrical load changes, since the alternator cannot follow such sudden changes.

Battery is an electrochemical device that stores electrical energy in chemical form. Whenever there is load demand, the chemical reactions takes place within the battery.

Structure of the Battery The automotive lead acid battery is generally made of six polypropylene walled cells. These cell elements are submerged in an electrolyte and connected in series from the positive terminal post to the negative terminal post. Each of the cell compartments consists of cell elements comprises of plates of dissimilar material, separators, and connecting links. The plates are formed by pasting soft material onto flat and sturdy, mesh-like grids constructed of a lead-calcium alloy [27]. Positive plates or electrodes are pasted with lead dioxide (PbO_2) form the positive plates (i.e., positive electrodes). The negative electrodes are made of sponge lead (Pb). The group of positive and negative plates alternatively interlaced form the cell element. A porous envelope separator is used between opposite polarities and this avoids the short circuit occurring with the contact between polarities [27]. The positive and the negative plates are connected to the positive and negative terminals posts of battery. Each cell can provide nearly two volts. Hence six cell automotive battery can provide 12V. Fully charged Battery will contain 36 percent of sulphuric acid and 64 percent water. The specific gravity of this electrolyte solution is 1.270. As the battery discharges, the electrolyte will be concentrated more with water molecules. Hence, the specific gravity lowers. Whenever the battery is charged, specific gravity of the electrolyte increases, and the original concentration of sulphuric acid and water is achieved. The measure of specific gravity is used in determination of battery state of charge (SOC) [27].

Chemical Reactions Whenever the battery discharges, the chemical reaction that takes place in between the electrolyte and each of positive and negative plates releases electrons. The process is given by [27]

$$Pb + PbO_2 + 2.H_2SO_4 \Rightarrow 2.PbSO_4 + 2.H_2O \tag{2.1}$$

As per equation (2.1) it can be seen that the sulphuric acid dissociates into sulphite ions and hydrogen. And, the lead from negative plates react with sulphite to produce lead sulphate $PbSO_4$. The lead dioxide from positive plates dissociates into lead and oxygen. The oxygen in turn combines with hydrogen ions in electrolyte and increases the concentration of water (H_2O). the sulphate ions which are oxygen free react with sulphate to form lead sulphate ($PbS0_4$). Therefore lead sulphate is produced both in positive and negative plates and increases water concentration in electrolyte. Hence the specific gravity decreases. Accumulation of lead sulphate hampers the chemical reaction, therefore completely the discharging the battery.

In case of charging phase, the above procedure is just reversed. Lead sulphate obtained in both the plates dissociates into lead ions and sulphite ions. Water dissociates into hydrogen and oxygen. The sulphate ions combine with the hydrogen to form sulphuric acid. Negative plate is hence maintained in original lead form. Lead ions in positive plates combine with oxygen to form lead dioxide. Therefore the reaction causes electrons to flow from negative to positive plate.

Battery monitoring is mainly needed to derive the best of the battery capability so as to guarantee the power supply for high reliability devices [19, 20]. In order to study the battery status (i.e, state of charge (SOC) and state of health (SOH)), the voltage, current and temperature are to be evaluated. Processing of this data is done in many ways using alternative approaches. For the study purpose, the mathematical model of vehicle electric power system (VEPS) can be considered. Each of these can be modeled as equivalent circuit [17]. Based on the inrush of current at the dawn of charging or discharging, batteries can be modeled by two equivalent circuit models. Battery model with capacitance (BWC) and Battery model without capacitance (BWOC). It was seen that the total amount of inrush current charge increases with the supply voltage and the ratio of inrush current charge to total charge decreases. BWOC is considered as an appropriate model for VEPS[17].

2.1.3 Load

The third important component of the EPGS system is the load. It mainly refers to the on board entertainment, lighting systems, climate control and other devices which makes use of the alternator current.

The electronic control units in the EPGS system (i.e., ECM and BCM) conduct electric power management operations. For instance, they adjust the alternator output voltage (i.e., battery charging voltage) based on the estimated battery state and control the battery's state-of-charge (SOC) to maximize fuel economy, generator efficiency and battery life.

2.2 Alternator Related Fault effect Analysis

In order to guarantee reliable electric power supply to the vehicular electrical system, faults in the EPGS system need to be accurately diagnosed as soon as possible to prevent any significant consequences and customer dissatisfaction. Based on warranty data analysis conducted by automotive OEM's, the most common alternator related faults in the automotive EPGS system are as follows.

- Shorted diode fault occurs when one or more diodes in the rectifier are broken and leads to continuous conduction of current. Consequently, the output of the alternator is no longer DC current/voltage. This is often caused by overvoltage during transient periods of vehicle operations.

- Regulator fault occurs when the regulator becomes defective and loses its regulation capability. Consequently, the duty cycle of the field PWM signal is locked at an unknown value between zero percent and hundred percent. Therefore, the alternator may produce excessive or insufficient current/voltage depending on the demanded current from electronic consumers. As a result, the battery may get overcharged or drained, and other electrical devices in the vehicle may get damaged.

- Belt slipping occurs when the drive belt between the alternator and engine pulleys does not have enough tension to keep the alternator pulley rotating synchronously with the engine shaft, which may be caused by the wearing of the drive belt or improper installation. Consequently, the alternator to engine speed ratio drops, which reduces the efficiency of the alternator. Therefore, the battery may need to discharge more frequently in order to supply additional power to meet the load current demanded. But, this in turn will reduce the battery's availability and service life.

EPGS Simulation model and Motivation

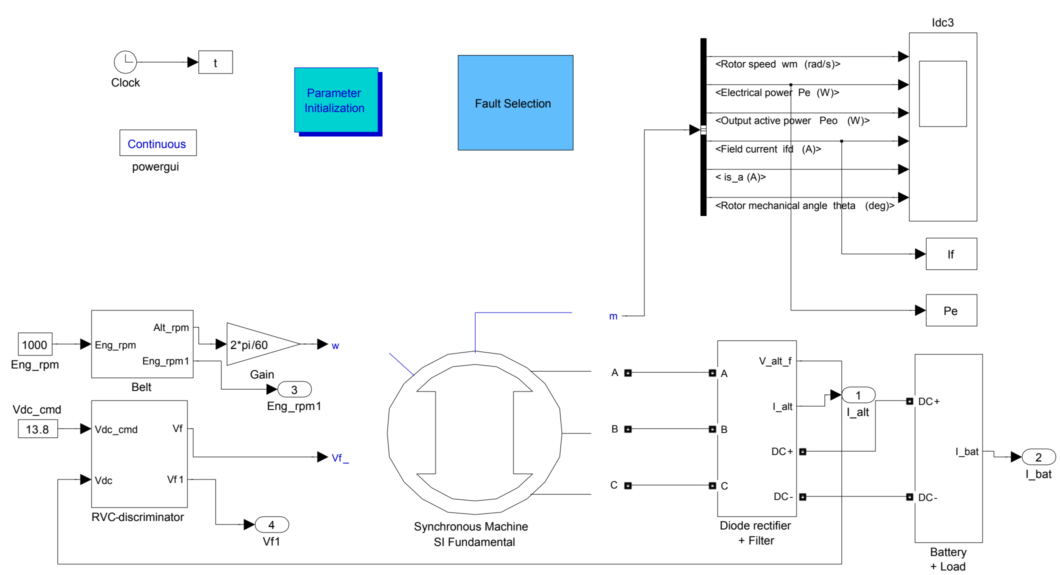

Figure 3.1: Simulink model of EPGS system

For the purpose of algorithm development and evaluation, a simulation model of the EPGS system was developed using Simulink, as shown in Figure 3.1. It can be divided into five parts, namely- voltage regulator, belt model, generator, rectifier and the load.

The belt model : The nominal belt ratio is 3:1 between the alternator and the engine rpm. The model is developed so as to fulfill this requirement.

Generator : In order to implement a rotor model, the synchronous machine block of Simulink Simpower systems library is being used. The input to the block is mainly the alternator rpm and field voltage from the regulator. More details about its operating principles can be seen in [30].

Diode rectifier and filter : This part of circuit mainly accomplishes the task of rectifying the alternator voltage into dc voltage. It also consists of a low pass filter to remove high frequency components. The rectification is achieved by means of diode bridge rectifier constructed by making use of six diodes.

Load and Battery : This part of the model defines the load profile and the battery. Load profile refers to current consumed by different electric devices. To simulate this, six switching loads operating at increasing order are used. The load profile depends on the number of switches and the time duration for which it is enabled. Maximum current is drawn when all the switches are in on state. A low pass filter is introduced at the battery and output terminals to remove noise components. At sudden electric load changes the current requirement is fulfilled by the battery until the alternator current stabilizes to required level.

Voltage regulator : The voltage regulator controls the output voltage of the alternator by controlling the amount of current provided to the rotor. In other words, the regulator generates a pulse width modulated (PWM) voltage signal that is applied to the alternator field winding. By changing the duty cycle of the filed voltage PWM signal, the average field voltage and the alternator output voltage can be controlled. The task is carried by comparing the output voltage with the given command voltage, and the field voltage required for the operation is generated by using a PI controller.

3.1 Motivation

In order to develop an effective fault diagnostic method, an initial study was conducted to investigate the effect of different faults on EPGS system signals. Figure 3.2 shows the comparison of engine rpm and alternator rpm signals between the normal operating condition and the case of belt slip.

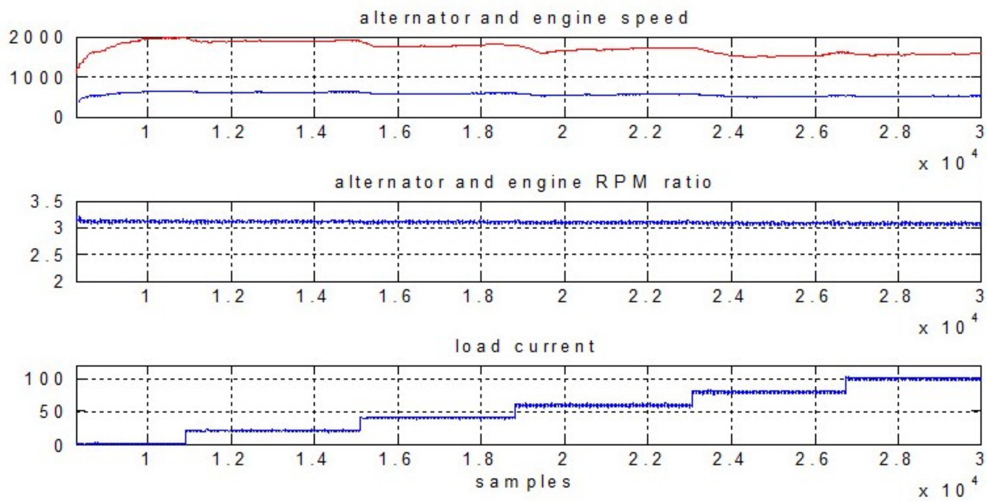

Figure 3.2: Alternator and engine RPM signals at normal operating conditions

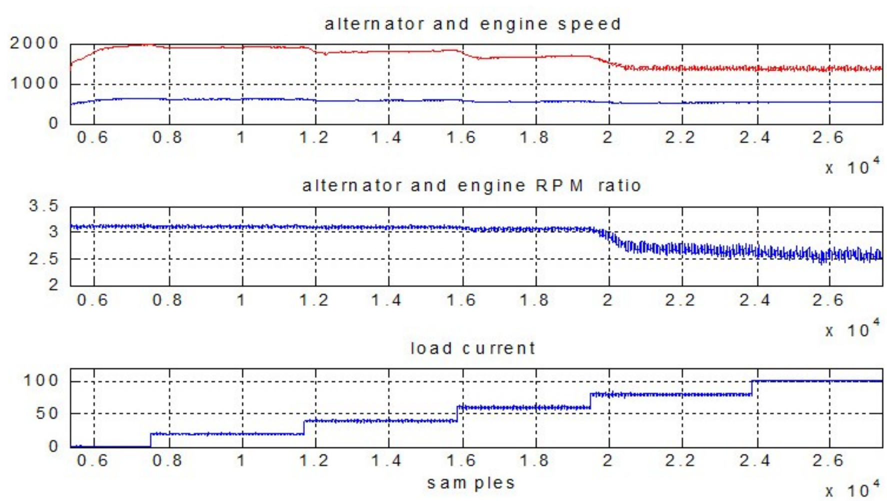

Figure 3.3: Alternator and engine RPM signals at belt slippage conditions

The engine speed was kept at approximately 500 RPM, and the same load current profile was used under these two conditions. Referring to third figure, the speeds of the engine (blue) and alternator (red), their speed ratio, and the load current profile are given in the first plot, second plot, and third plot, respectively. From the second plot of Figure 3.3, it can be seen that the effect of belt slippage only shows up at the time corresponding to high load current (or equivalently, high alternator field duty cycle). Specifically, the alternator to engine speed ratio drops from 3.1 to approximately 2.5. As the current demanded from the alternator by the load increases, the torque required to move the alternator rotor also increases. When the required torque exceeds the maximum friction of the drive belt, slippage will occur if the tension of the belt is improper. Consequently, the alternator to engine RPM ratio drops.

Based on the above observation, it is concluded that, in order to effectively diagnose the belt slippage fault, the dynamics of the system with high field voltage duty cycle should be considered. Additionally, from the second plot of Figure 3.3, we can see that the effect of belt slippage does not show up with low load current (or equivalently, low field voltage duty cycle). This feature can be used to isolate the belt slippage fault from other faults which affect the system signals all the time (for instance, the shorted diode fault).

Based on the above discussions, the fault detection and isolation (FDI) logic shown in Table 1 is proposed, where a '0' indicates the diagnostic residual is low, a '1' indicates the diagnostic residual is high, and a 'x' means the value of the residual does not affect the diagnostic results. Residual 1 is generated based on a parity relation characterizing the normal system dynamics at low filed voltage duty cycle (for instance, 20% to 60%), and residual 2 is generated by a parity relation characterizing the normal system dynamics at high field duty cycle (for instance, 100%). Additionally, residual 3 is specifically designed for regulator fault diagnosis.

The regulator is mainly designed to control the battery voltage V_{bat} and to track the reference voltage V_{ref} by adjusting the duty cycle of the field voltage PWM signal. If the

Fault scenarios	Residual 1	Residual 2	Residual 3
Normal	0	0	0
Belt Slip	0	1	0
Diode Short	1	1	0
Regulator Fault	X	X	1

Table 3.1: Fault detection and isolation logic

regulator is "$healthy$" and the field voltage duty cycle is less than 100%, V_{bat} should be very close to V_{ref} (because the regulator is still able to regulate). Additionally, when the field voltage saturates as a result of high current demand from the consumers, V_{bat} should be lower than V_{ref}. Therefore, in order to effectively detect and isolate the regulator fault, residual 3 is set to "1" if any of the following conditions are satisfied:

- The field voltage duty cycle is less than 100 percent, and the battery voltage V_{bat} is significantly lower or higher than the reference voltage V_{ref}. This corresponds to the case that the field voltage duty cycle is stuck at a value of less than 100%.

- The field voltage duty cycle is 100%, and the battery voltage V_{bat} is significantly higher than the reference voltage . This corresponds to the case that the field voltage duty cycle is stuck at 100% (i.e., shorted to system voltage). It is worth noting that, during typical driving cycles, most of the time the field voltage duty cycle does not saturate (this is the criterion used to select appropriate alternator type for specific vehicle platform). Therefore, under such conditions, a regulator fault with field voltage duty cycle stuck at 100% will produce an excessively higher voltage than the reference voltage.

3.2 Residual Generation

In the fault diagnosis literature, the quantitative model-based fault diagnosis method has attracted significant attention [3, 24, 9, 13]. Considerable effort has been devoted to fault diagnosis of nonlinear systems under various kinds of assumptions and fault scenarios (see, for instance, [25, 32] and the references cited therein). In general, a residual is defined as the discrepancy between an actual sensor measurement and its estimation obtained from a mathematical model of the nominal system dynamics. Then, the residual is compared with a threshold to determine fault diagnostic decisions. Quantitative model-based fault diagnostics have been shown to be successful in many applications [22]. However, the EPGS system is a highly complicated nonlinear dynamic system with very limited sensor measurements. For the alternator, the combination of the highly nonlinear dynamics of the three-phase AC generator with the discontinuous switching behavior of the diode bridge rectifier, make the identification and calibration of an accurate physical dynamics based mathematical model very challenging. Moreover, the limitation of sensor measurements makes this issue even more challenging. For instance, in [5], an alternator EMF estimation method utilizing sliding mode observer techniques is presented based on the availability of a sensor measuring alternator phase current, which is not available in real-world automotive applications. Data-driven statistical approaches have also been widely used in health monitoring of complex industrial plants, where a good physics-based system model is not available [9, 31]. hence, we adopt a data-driven fault diagnostic method for generating the parity relations and the structured residuals described in Table 1, specifically, the well-known principal/minor component analysis method is used.

3.3 Principal component analysis (PCA)

As mentioned before, the EPGS system is a highly complicated nonlinear dynamic system with very limited sensor measurements. Moreover, the limitation of sensor measurements makes the task of fault diagnosis even more challenging. With the available process data such as engine rpm, battery voltage, field voltage and estimated alternator current, Process monitoring based on multivariate state analysis of process data is one of popular approach used in industrial process control. And, Principal component analysis(PCA) is one of well known technique used in this approach. Therefore, PCA technique would be used for fault evaluation in research.

Principal component analysis (PCA) is a multivariate statistical approach to analyze data sets with significant redundant information [9, 22, 29]. Its main function is to retain the most important characteristics of its input by using a small amount of vectors, i.e., the principal components. This technique has been applied to many applications including signal processing, data transmission and storage, and pattern recognition, and fault diagnostics.

Consider the sensor data to be a qXk matrix, where each row represents an observation. Let us denote p_i as the loading vectors [15], where$i < k$. The first principal component is defined as the linear combination $t_1 = Xp_1$ that has the maximum variance subject to $|p_1| = 1$. The second principal component is the linear combination defined by$t_2 = Xp_2$ that has the next greatest variance subject to $|p_2| = 1$ and subject to the condition that p_2 is orthogonal to the first loading vector p_1 . Up to k principal components can be similarly defined. Suppose the first N principal components capture an adequate approximation of the matrix x. Then, we define the last $k - N$ component as minor components. Based on the above discussion, PCA decomposes the x matrix as

$$X = \sum_{n=1}^{N} t_n P_n^T + \sum_{m=N+1}^{k} t_m p_m^T \tag{3.1}$$

where t_n and t_m ,$n = 1, ...N$, and $m = N + 1....k$,are the principal components and minor components respectively, and are the corresponding loading vectors. Denote $T \triangleq (t_1, ...t_N), \tilde{T} \triangleq (t_N + 1...t_k), P \triangleq (p_1, ...p_N)$, and $\tilde{P} \triangleq (p_N + 1...p_k)$. Then (Equation 3.1) can be rewritten as:

$$X = TP^T + \tilde{T}\tilde{P}^T \tag{3.2}$$

Using the orthogonality of matrices P and $\tilde{P}$, we have

$$X\tilde{P} = \tilde{T}\tilde{P}^T = \tilde{T} \approx O_{qX(k-N)} \tag{3.3}$$

where the entries of $\tilde{T}$ are minor components that are usually very small, as defined above. The residual model given by (Equation 3.3) can be used to generate parity relations characterizing the correlation among EPGS system signals under normal operating conditions. Specifically, sensor data collected under normal operating conditions is collected and used to obtain the matrix $\tilde{P}$ off-line by utilizing the PCA/MCA method. Then, new sampled sensor data can be processed on-line to generated diagnostic residuals using (Equation 3.3). If the system is operating under normal operating conditions, the correlation among system signals remains unchanged, and the output of the parity relation should be close to zero. In the presence of a fault, the system dynamics (and consequently the correlation among system signals) will change, therefore, the corresponding residual will significantly deviate from zero.

Hence by making use of novel residual evaluation scheme along with multivariate statistical technique -Principal Component analysis (PCA) an efficient algorithm can be developed which can help to achieve fault evaluation.

Fault Diagnosis Algorithm Performance and Results

In the previous sections, the EPGS system architecture and the faults associated with them were studied. Also, the technical approaches that can be used to identify the faults were introduced. Data-driven approach was seen to be one of the efficient ways that can be used in the diagnosis of EPGS system, and therefore this technique is used to develop the algorithm required for fault diagnosis. Using the simulation model as explained in Chapter 3, fault is introduced in the system. The residuals are hence obtained by using data with the algorithm developed in Chapter 3. Fault isolation is achieved based on technique explained in table 1.

4.1 Fault Injection

In order to diagnose the alternator faults, the deviations from normal operations of each of sub-models are to be introduced in the simulation model. After the careful study made on the EPGS system, the common faults were mainly found in drive belt, rectification circuitry, and the voltage regulator as discussed in Chapters 2 and 3. Figure 4.1 shows the simulink layout developed for fault injection. Whenever the parameter is checked, the corresponding fault (as labeled) is introduced.

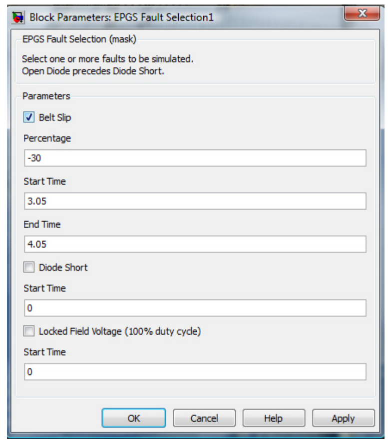

Figure 4.1: Fault injection in EPGS simulation model

Whenever the Belt slip is checked, the slip profile is introduced during the simulation. Whenever the slip profile is enabled the nominal belt ratio is reduced to 2.1 at high load conditions (i.e., the engine to alternator rpm is maintained at the value of 2.1).

The second type of fault that is being considered is the faulty diode in rectification circuit. The rectification is the process of converting alternating voltage which is obtained at the intervals of 60 degrees phase difference (at three different terminals of the rotor) to DC. Six diodes are used in bridge circuit. Two kinds of diode faults can occur: open diode, causing loss of DC voltage corresponding to one of the phase of alternating current, and diode short, leading to irregular rectification of alternating signals.

When locked field voltage is checked, the regulator fault is introduced in the model. In this simulation model, the case when the field voltage duty cycle locked at 100% is considered. This is achieved by letting field voltage always equal to the battery voltage.

4.2 Data Generation

The simulation results at normal operations are obtained from the EPGS Simulink model, by not injecting any kind of faults. The input to this system is the engine rpm and the load. Figure 4.2 shows the engine and alternator rpm at normal conditions. It is seen that the ratio of 3:1 is maintained between the alternator and the engine RPM at normal conditions. Under normal conditions it is considered that there is no wear and tear of belt. Hence

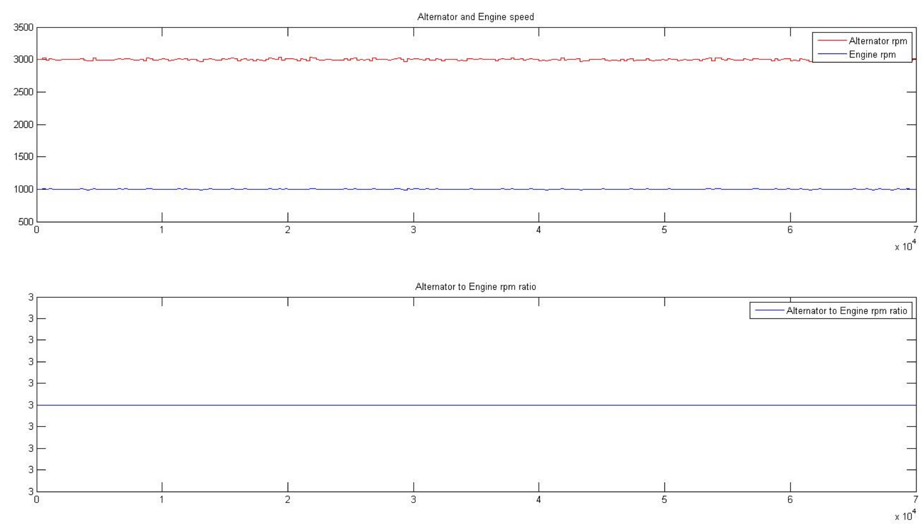

Figure 4.2: Engine RPM, Alternator RPM and Alternator to Engine RPM ratio

the engine rpm is effectively transferred to the alternator. Figure 4.3 shows the current profile and field duty cycle along with load variation. It can also be seen that at high load conditions the duty cycle reaches 100%. Another important observation that can be made is, at the transients or in other words the sudden increase in electrical loads, the battery supplies the required current until the alternator current reaches to expected level. Due to this, the battery rapidly discharges whenever the load increases and then starts charging to

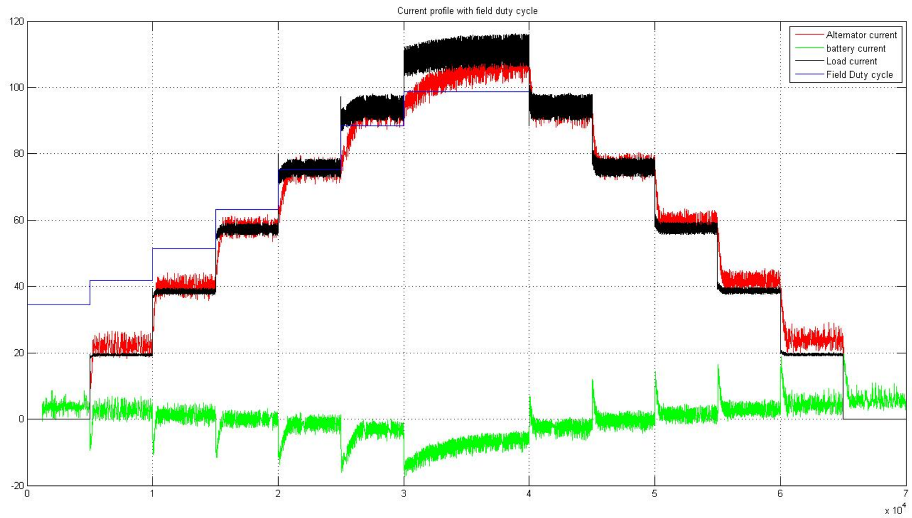

Figure 4.3: Alternator, load and battery current profile along with field duty cycle for varying load under normal conditions

original form as the alternator current builds up.

4.3 Parity relation training using PCA/MCA

On analyzing the data collected from the simulation result under normal conditions, a strong correlation among the engine speed, the alternator output current, the alternator field voltage, and battery current signals were observed. Due to this correlation between signals, principal/minor component analysis (PCA/MCA) can be used as an efficient tool as discussed before to generate parity relations to detect and isolate the different types of fault that occur in the EPGS system. The detection and isolation of faults in the EPGS system can be achieved by using the correlation among system signals to generate diagnosis residuals. The alternator output current will not depend on the field voltage once it reaches 100% duty-cycle, and since the effect of belt slip is only detected when the field voltage duty-cycle is very high, it is necessary to create two residual models of the healthy EPGS system: one model when the field voltage duty-cycle is low (say 40% -60%) and another model when the field voltage duty-cycle is high (say 80%-100%). The steps involved in determining the principal/minor component models for normal conditions are as follows

1. The first step towards the PCA analysis is to obtain the correlated system signals, which includes the engine rpm, alternator current and field voltage at low field duty cycle.

2. Referring to Figure 4.3, the sudden variation in battery current is observed whenever the load increases. Hence the time instants at which load changes is determined by finding change in battery current.

3. With the help of time instants obtained, the values of engine rpm, alternator current and field voltage between the segments (cornered by successive time instants determined) corresponding to low duty cycle are extracted.

4. The extracted values are then normalized to the range [-1, 1] and, this set of normalized data forms a data matrix related to low field duty cycle.

5. The eigen vectors are found by computing the correlation matrix of the data obtained previously, from the simulation results of the EPGS system working under normal conditions. To take the system dynamics into account, each signal sample can be redistributed to have twice as many sets of data samples.

6. The principal and minor components are obtained by comparing the eigen values of the correlation matrix. i.e. the eigen vectors corresponding to the large eigen

values form loading vectors corresponding to the principal components (i.e.P, in (Equation 3.2)), and the remaining eigen vectors corresponding to the smaller eigen values of the correlation matrix form the loading vectors corresponding to the minor components.(, i.e.$\tilde{P}$,in Equation 3.3).

7. The effect of belt slip is only seen in high load conditions. As mentioned before, it is necessary to create two residual models. In order to achieve this, the PCA/MCA analysis must be carried at high field duty cycle (100%) conditions. Therefore, the steps 4 to 6 are repeated with only difference of being selective of data. (i.e. all the signals mentioned in step 1, corresponding to high field duty cycle is to used).

The PCA/MCA analysis hence results with two different minor component models, i.e one corresponding to low field duty cycle (hereafter referred as minor component model 1) and the second for high field duty cycle (hereafter referred as minor component model 2). These components serve as the basic foundation for the residual generation which is discussed in the next section.

4.4 Evaluation Results

The section mainly focuses on the details of how fault diagnosis is carried on and the residuals can be obtained for different faults under consideration. In previous section, the PCA analysis for the sensor data under normal conditions was conducted, the loading vectors corresponding to minor components were hence derived. In this section, the generation of diagnosis residuals for normal conditions will be discussed. Also, the investigation of faults occurring would be carried by making use of the algorithm that is developed.

4.4.1 Normal Conditions

Under normal conditions, the nominal engine rpm to alternator rpm ratio is always to be maintained at 3:1. The effect of belt slip is always seen in high load conditions or when the field duty cycle is high. Based on this, the PCA/MCA analysis was being carried on, and the loading vector corresponding to minor components (i.e.,$\tilde{T}$) were obtained for the two residuals. The steps involved in residual generation are as follows

1. The correlation matrix corresponding to low field duty cycle is projected onto minor component model 1. The magnitude of this projected data gives the diagnosis residual 1, under normal conditions.

2. On the similar lines the analysis is carried on the data corresponding to high duty cycle using minor component model 2, which results in diagnosis residual 2 under normal conditions. Figure 4.4 and Figure 4.5 shows two residuals obtained under normal conditions.

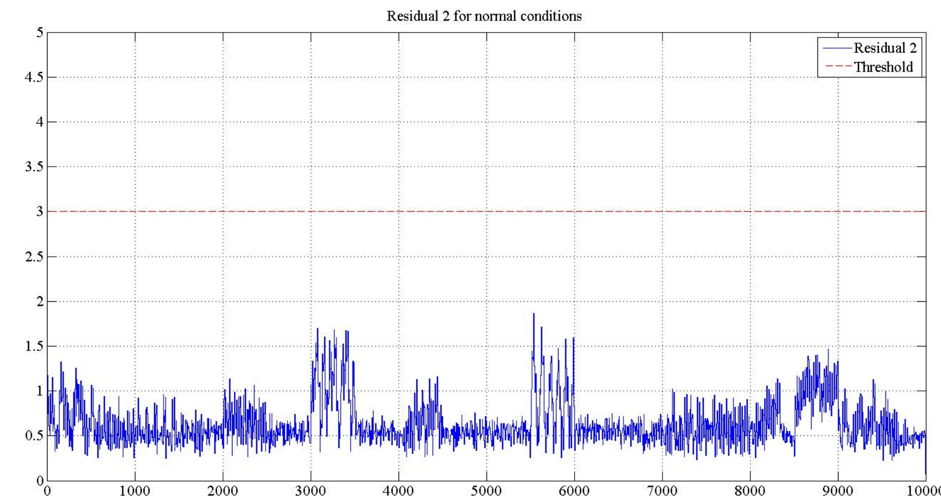

Figure 4.5: Residual 2 at normal condition

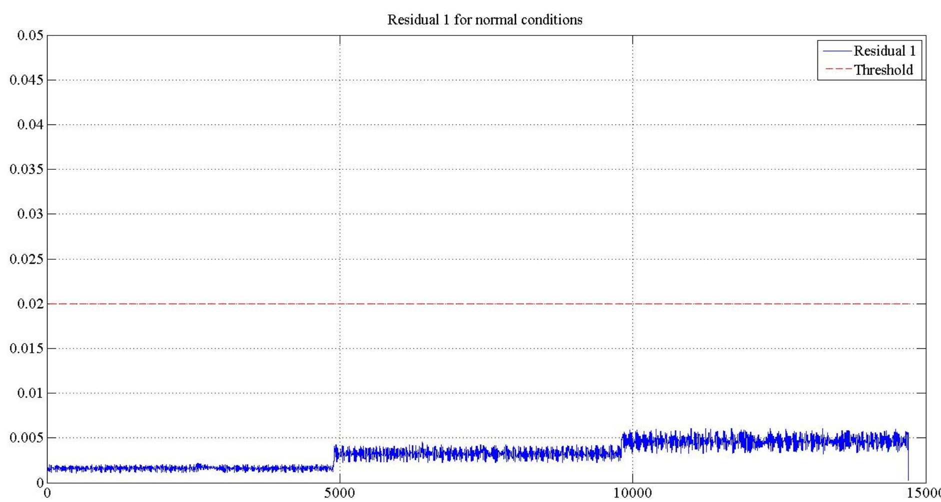

Figure 4.4: Residual 1 at normal condition

4.4.2 Belt Slipping

As shown in Figure 4.6, whenever a belt slippage occurs, the nominal belt ratio of 3:1 is no more maintained. By referring Figure 4.7, which shows the battery current (green), load current (black) the alternator current (red) and the field duty cycle (blue), obtained at normal and faulty conditions - it can be seen that the belt slip affects the alternator current at high load conditions or when the field duty cycle is high. Therefore, the maximum alternator current is lesser than that at normal conditions.

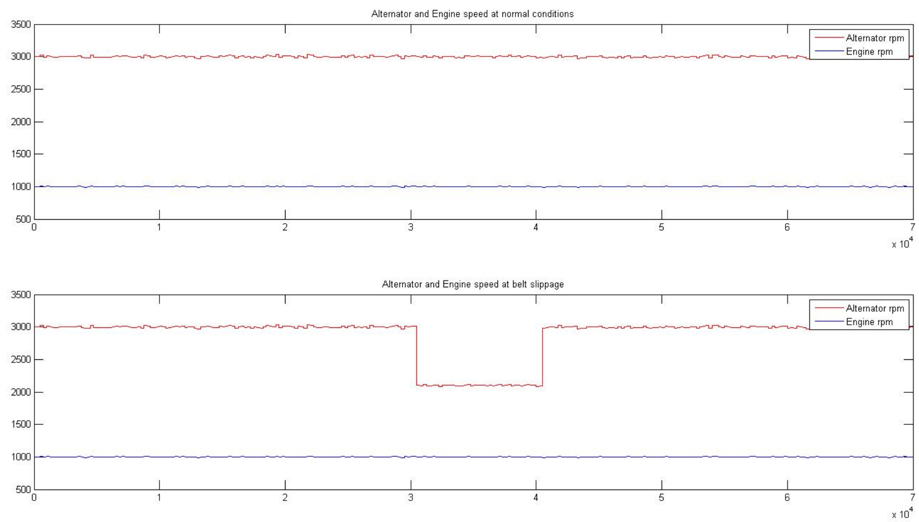

Figure 4.6: Engine and Alternator rpm at normal and belt slip conditions

The residual models 1 and 2 are obtained in a similar manner as discussed before for normal conditions. The correlation matrix comprising of alternator current, engine rpm and field voltage, corresponding to low field duty cycle and high field duty cycle are obtained separately. The residuals are obtained by projecting the correlation matrix onto respective minor component models. The magnitude of projected data would give the diagnosis residual 1 and residual 2 respectively. As seen from Residual 1 and 2 responses for the belt slipping fault in Figure 4.8 and Figure 4.9, the residual 1 remains same as for normal conditions. But, the residual 2 response is much higher than the normal condition (threshold), stating the occurrence of belt slip. This is consistent with the FDI logic given

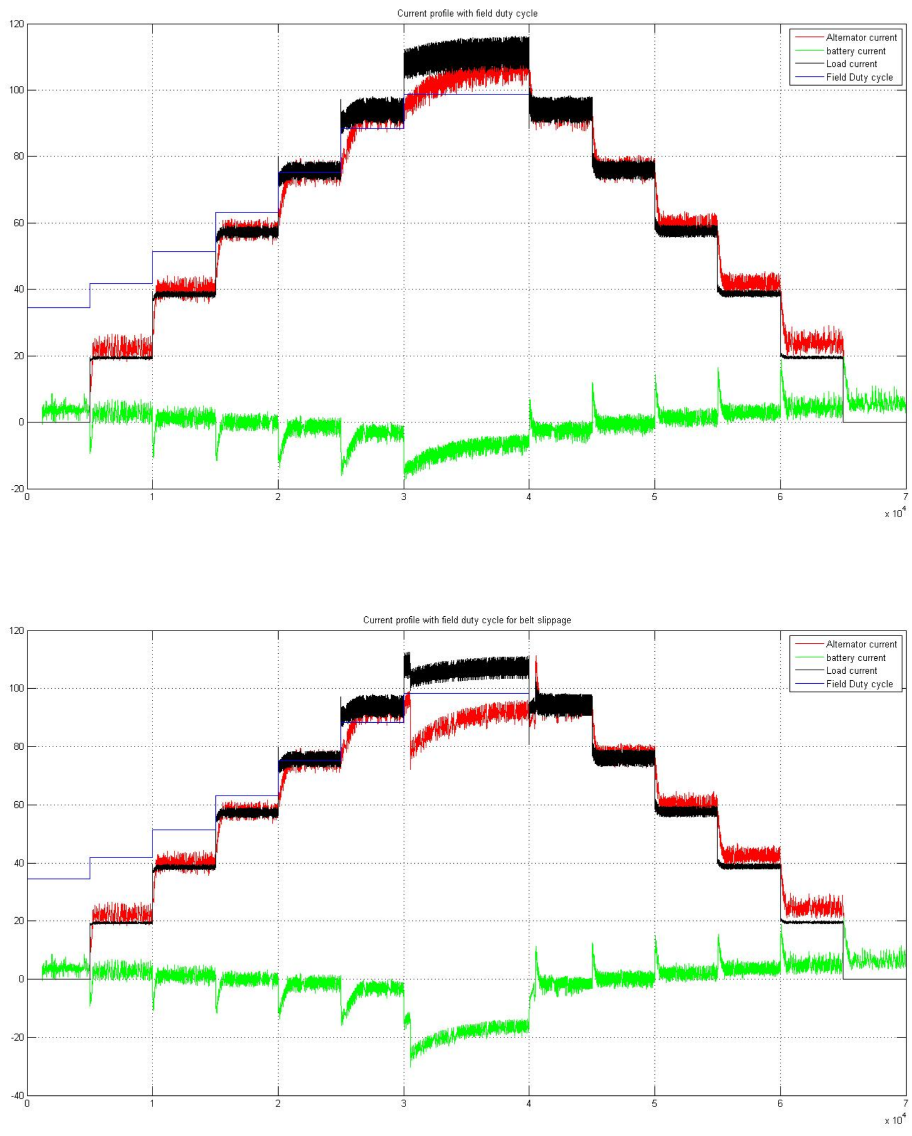

Figure 4.7: Current profiles and field duty cycle at normal and belt slip conditions

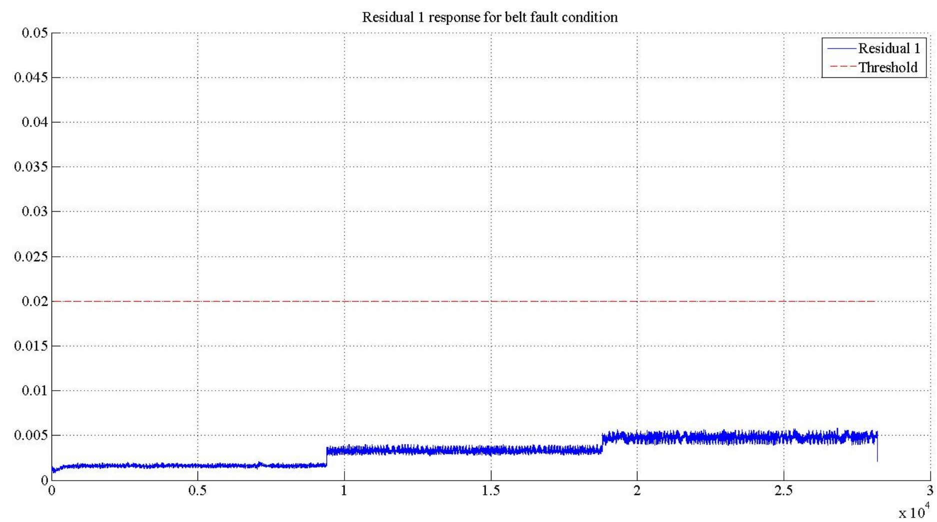

Figure 4.8: Residual 1 under belt slip condition.

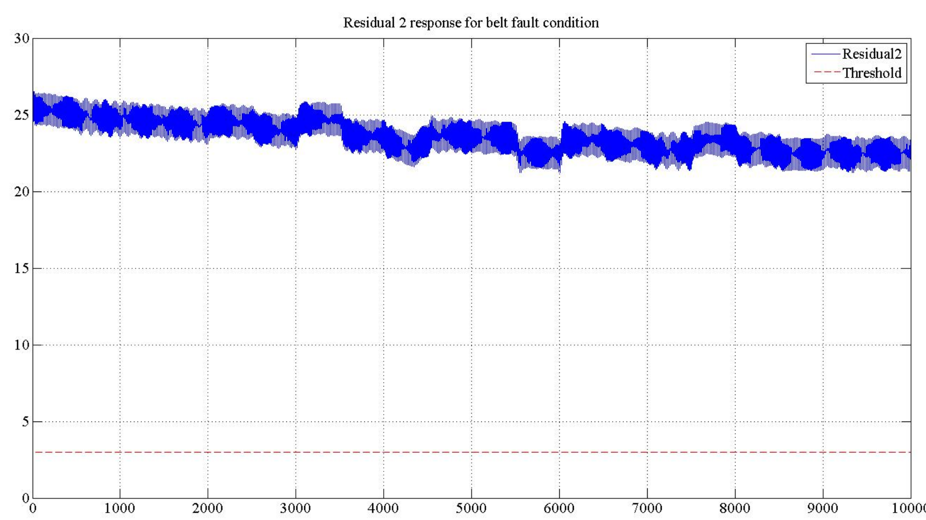

Figure 4.9: Residual 2 under belt slip condition.

in Table 1. Hence this model serves an efficient way for detection and isolation of belt slip in the EPGS system.

4.4.3 Diode Short

Another important fault that occurs in alternator of EPGS system is the diode fault. Using the same technique of residuals it is possible to detect the occurrence of the fault. The loading vector corresponding to minor components (i.e., $\tilde{T}$) that were obtained from the normal data are used for the diagnosis. In case of belt slip, the current profile with alternator and the load current showed that they almost followed each other except for at high duty cycle at faulty condition. With the occurrence of diode fault it is very much different. Whenever the fault occurs in the rectifier, the alternator will not be able to provide required current to the load. In order to fulfill the load requirements the battery starts providing the additional required current and hence gradually discharges. The current profile in Figure 4.10 explains the scenario of the alternators inability to provide load current and hence the battery discharges to satisfy the load requirement

With the effects of the faulty diode being studied, the FDI algorithm is to be verified. The minor component models 1 and 2 obtained previously is being used to generate the residuals. The residual models 1 and 2 are obtained in the similar way for the correlation data as obtained under normal and belt slip condition. Under faulty conditions, the magnitude of the projected correlated data will be greater than magnitude of projection under normal conditions. Figure 4.11 and Figure 4.12, shows the residual responses diode fault (red) and normal conditions (blue). It can be seen that for the case with diode fault, both

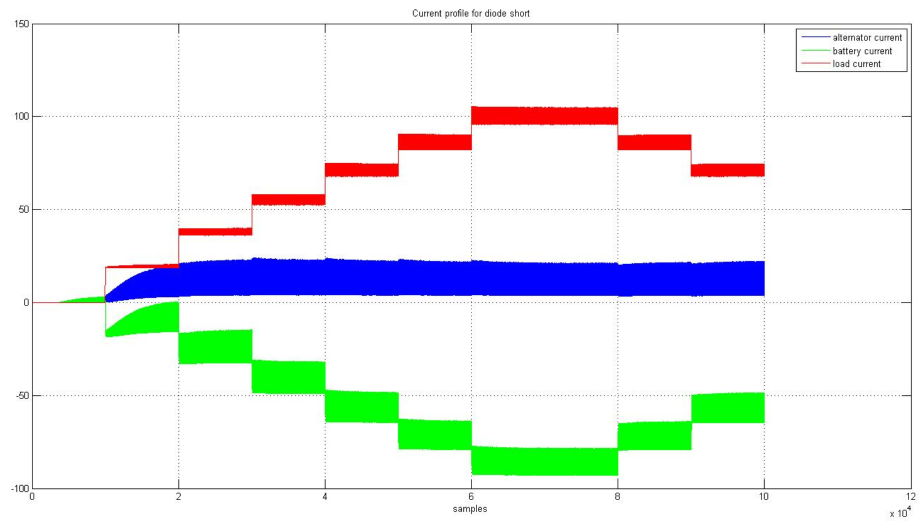

Figure 4.10: Current profile for shorted diode condition

the residuals are greater than normal conditions. Since the diode fault results are also consistent with the FDI logic given in Table 1, the diagnostic model serves an efficient way for detection and isolation of diode faults in the EPGS system.

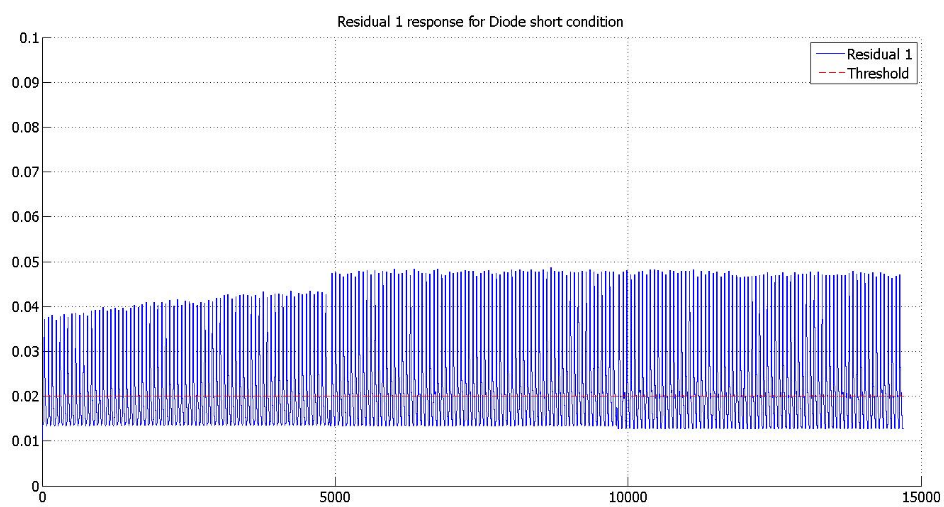

Figure 4.11: Residual 1 under diode fault condition

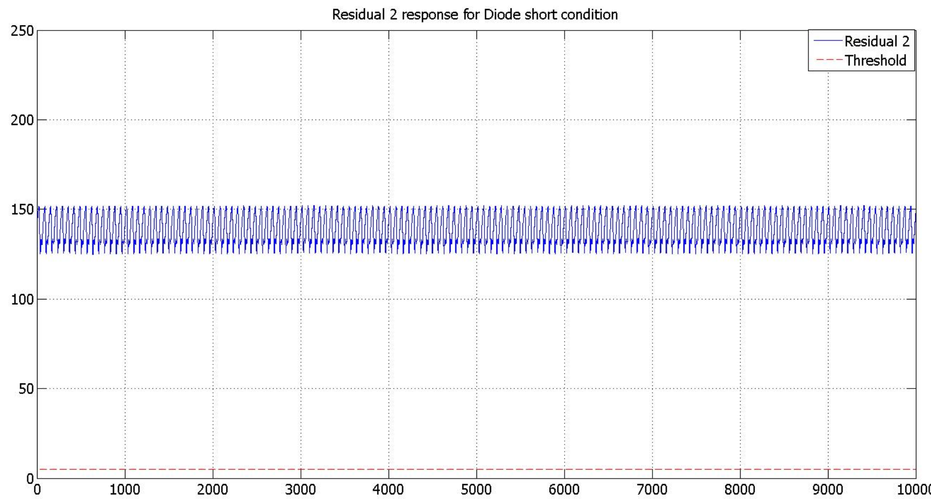

Figure 4.12: Residual 2 generation under diode fault condition

4.4.4 Regulator fault

As discussed in Chapter 3, the regulator fault can be determined without making use of Principal component model. And, instead a different approach can be used. Figure 4.13 shows the current profile with the field duty cycle at regulator fault conditions (fixed at 100% duty cycle). It can be observed that initially, the alternator current increases based on the load requirement under normal conditions. When the fault occurs (at approximately sample 1089 in figure Figure 4.13), the alternator current no more increases with the load requirement, and instead it tends to reach the maximum value. This is mainly because that, with the regulator fault, the field voltage duty cycle is fixed at 100% or produces same output voltage as the battery voltage. Hence the regulator is termed as 'locked' due to its inability to meet the required field duty cycle. Figure 4.14 compares the actual battery voltage with the reference voltage under regulator fault conditions. As can be seen, due to the locked field voltage, the battery voltage can no longer track the reference voltage.

Hence by considering the results obtained from Figure 4.13 and Figure 4.14, the FDI logic developed for the voltage regulator fault in Chapter 4 can be successfully applied.

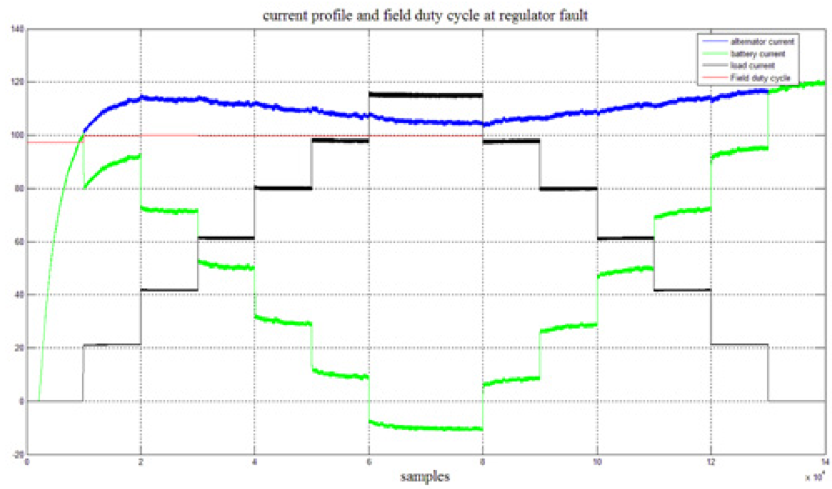

Figure 4.13: Current profile and field duty cycle at the regulator fault condition

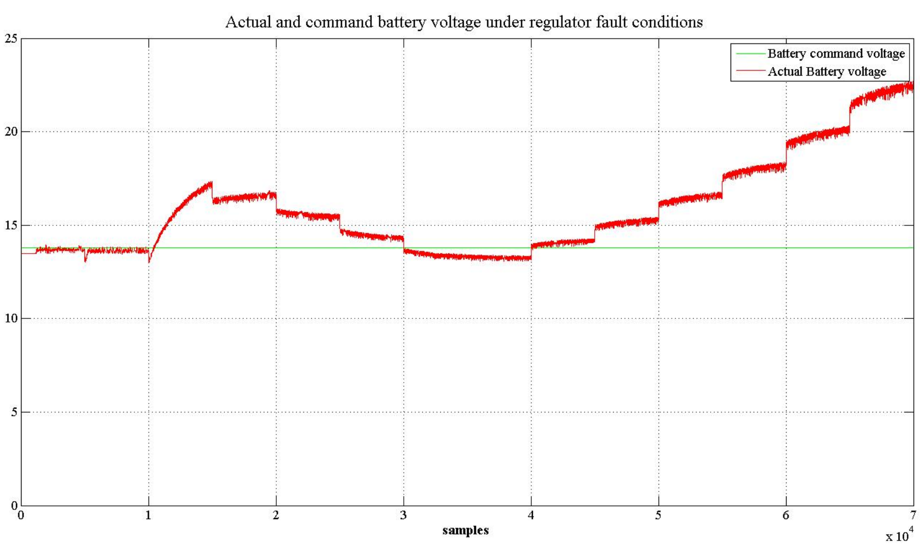

Figure 4.14: Battery terminal voltage compared with the command voltage at regulator fault condition

Online Fault Diagnosis

The fault diagnosis for EPGS system discussed in previous chapter mainly focused on offline technique. In order to make the algorithm functional for real-time application, it is necessary to implement the algorithm in a recurrsive manner. The simulation model for the online fault diagnosis of EPGS system was developed using Simulink, as shown in Figure 5.1. It can be divided into three major parts, namely- EPGS block as explained in chapter 3, the preprocessing block and the residual generator. The fault injection is being carried in a similar manner as described in chapter 4

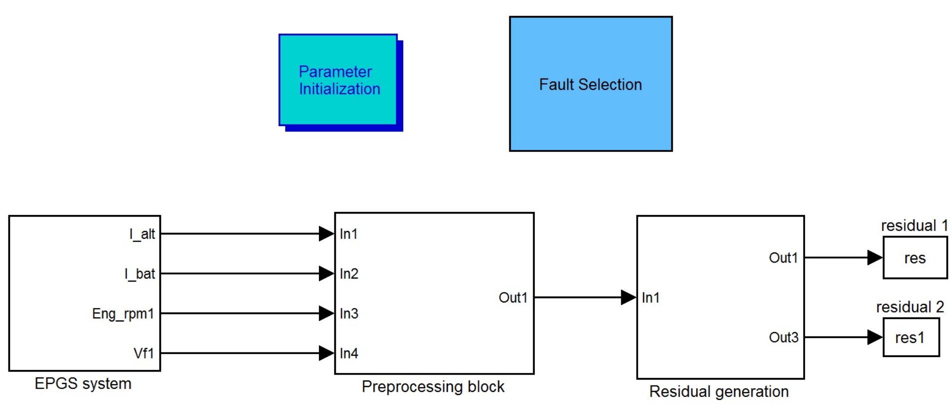

Figure 5.1: Online Fault diagnosis of EPGS system

5.1 Pre-Processing

In chapter 4, the principle component analysis was carried on the basis of correlation among system signals at steady state conditions. The field voltage generated by the action of voltage regulator is basically in the form of pulse width modulated signals. This was in turn converted to dc signal by means of averaging the pwm waves during steady state conditions. In real-time application, this task can be accomplished by making use of a low pass filter or by averaging technique. Hence the main task of preprocessing block is to average the parameters such as engine rpm, field voltage, and alternator current to reduce the effect of noise and transients.

5.2 Residual Generation

Figure 5.2 shows that, the nominal engine rpm to alternator rpm ratio is always maintained at 3:1 under normal conditions. Figure 5.3 shows the current profile with field duty cycle under normal conditions. The PCA/MCA analysis was being carried out, and the loading vector corresponding to minor components (i.e.,$\tilde{T}$) were obtained for the two residuals, as discussed in the chapter 4. Using the same techniques, the correlation matrix corresponding to low field duty cycle is projected onto minor component model 1. The magnitude of this projected data gives the diagnosis residual 1. And on the similar lines the analysis is carried on the data corresponding to high duty cycle using minor component model 2, which results in diagnosis residual 2. Figure 5.4 and Figure 5.5 shows the residuals obtained under

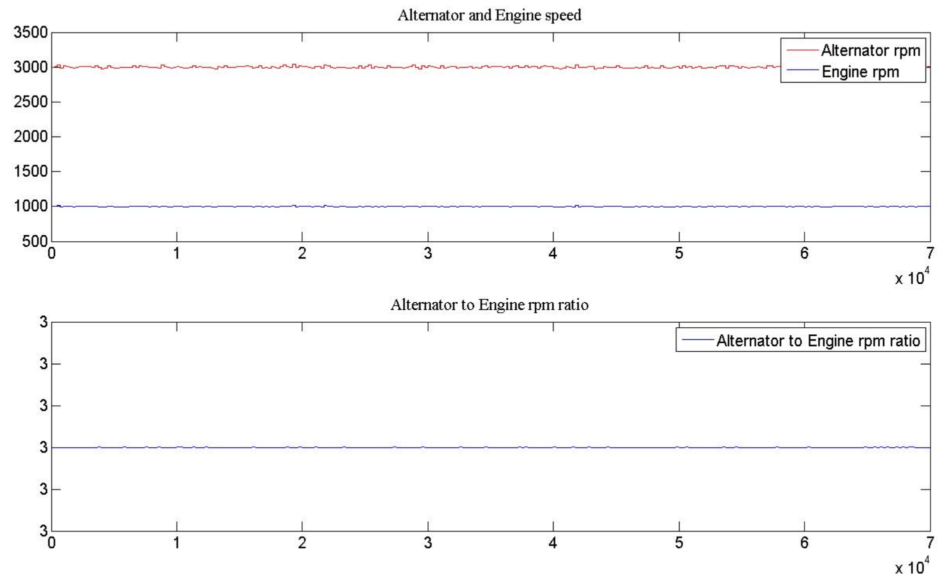

Figure 5.2: Engine to Alternator rpm ratio

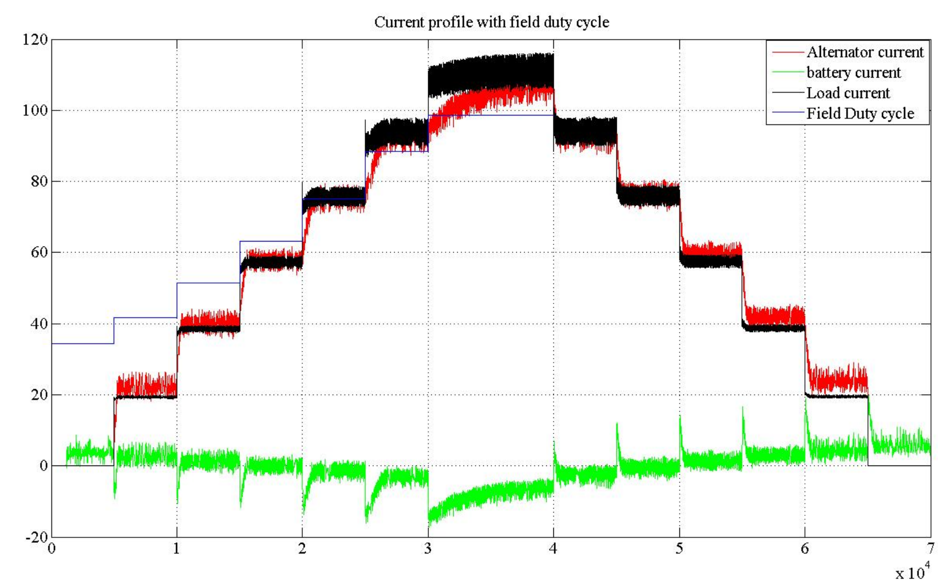

Figure 5.3: Current profile with field duty cycle under normal conditions

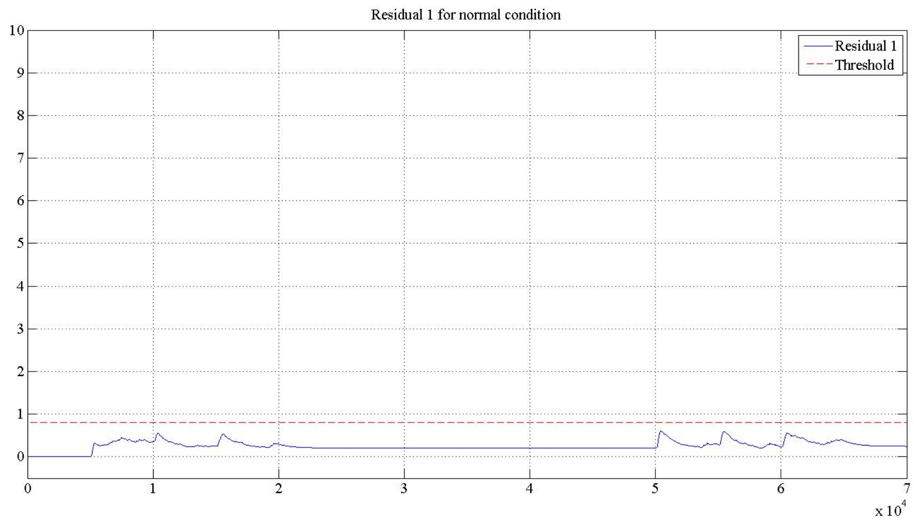

Figure 5.4: Residual 1 under normal conditions

normal conditions. As expected, both the residuals remain below thier thresholds.

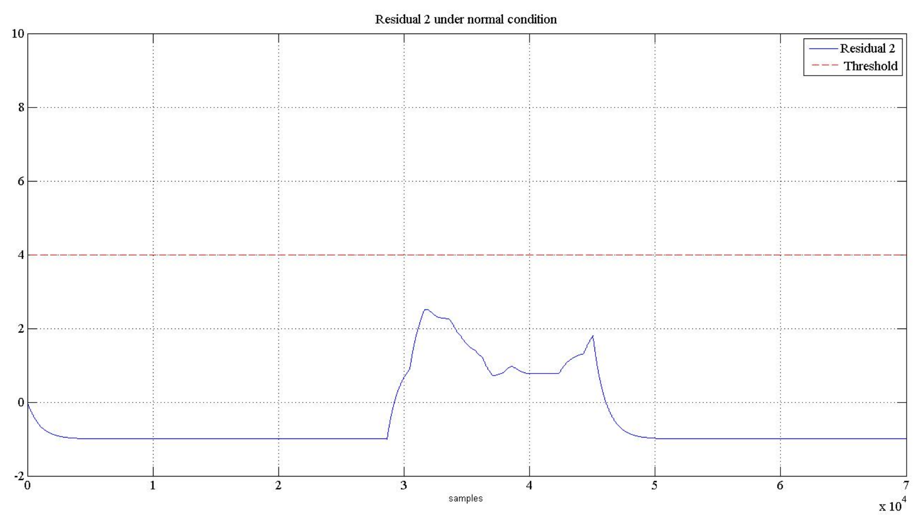

Figure 5.5: Residual 2 under normal conditions

5.2.1 Belt slip

From Figure 5.6, it can be seen that, whenever a belt slippage occurs, the nominal belt ratio of 3:1 is no more maintained. By referring Figure 5.7, it can also be seen that the belt slip affects the alternator current at high load conditions or when the field duty cycle is high. Hence, the maximum alternator current is lesser than that at normal conditions. The residuals for belt slip are obtained on the similar lines as carried on for normal conditions. It can be observed that whenever the fault occurs, the magnitude of the projected data will be greater than that for the normal conditions. Figure 5.8 and Figure 5.9, shows the residual responses at belt slip condition. It is observed that Residual 2 exceeds the threshold whereas residual 1 remains within threshold limits, indicating the occurrence of belt slip. This is consistent with the FDI logic given in Table 1 and offline model results. Hence the model serves an efficient way for detection and isolation of belt slip in the EPGS system.

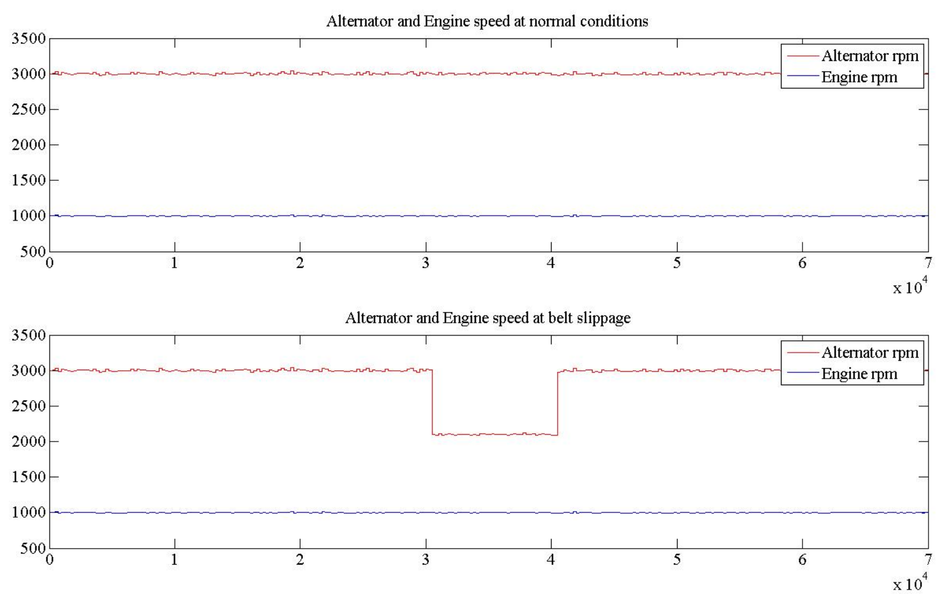

Figure 5.6: Engine to Alternator rpm ratio under belt slip conditions

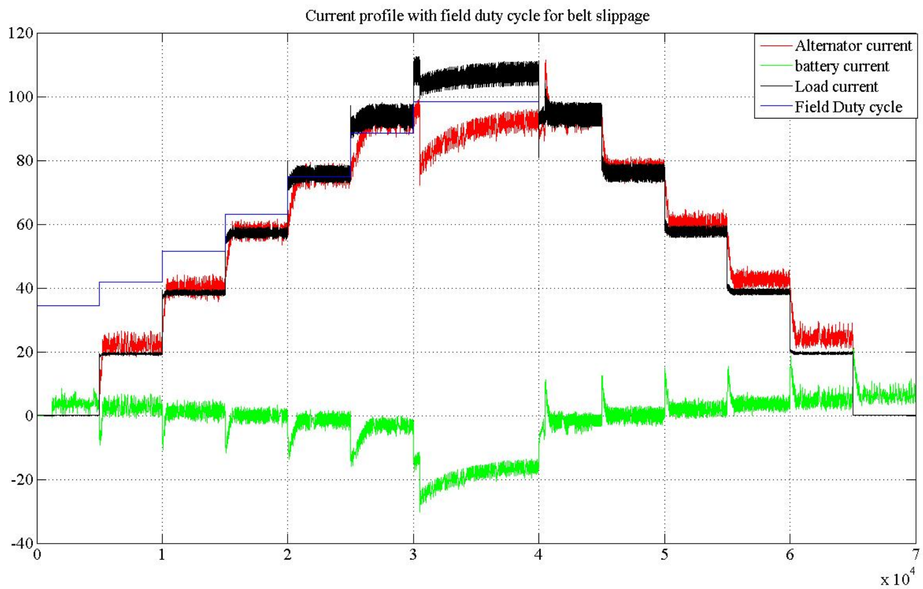

Figure 5.7: Current profile with field duty cycle under belt slip conditions

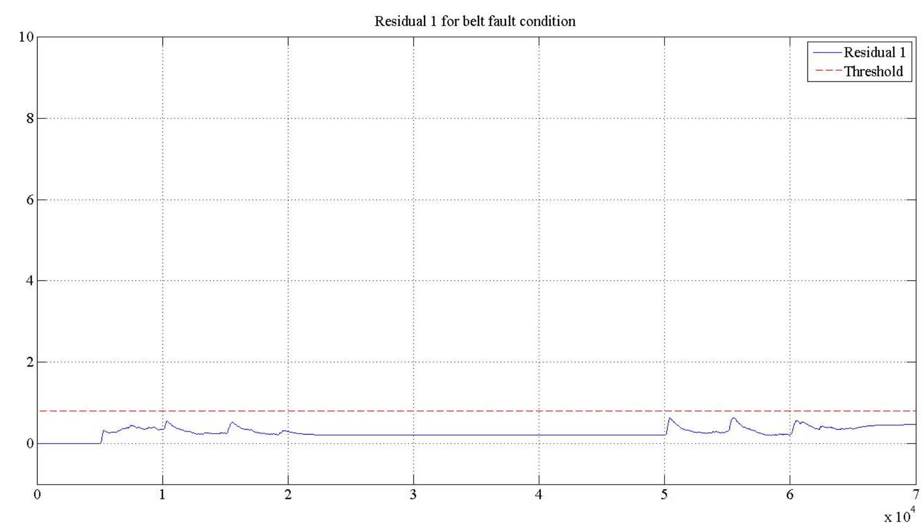

Figure 5.8: Residual 1 under belt slip conditions

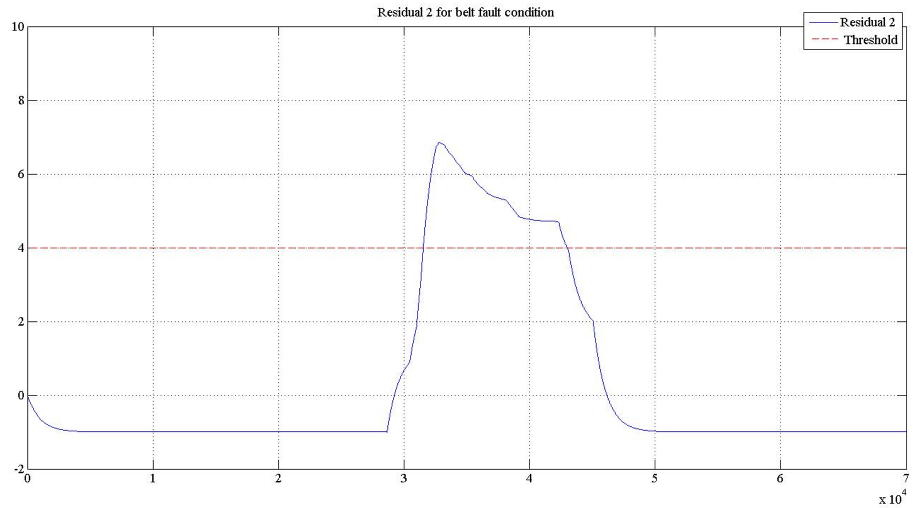

Figure 5.9: Residual 2 under belt slip conditions

5.2.2 Diode Short

Another important fault that occurs in alternator of EPGS system is the diode fault. Using the same technique of residuals it is possible to detect the occurrence of the fault. Figure 5.10 shows the current profile under diode short conditions. Whenever the fault occurs in the rectifier, the alternator will not be able to provide required current to the load. In order to fulfill the load requirements the battery starts providing the additional required current and hence gradually discharges.

The residual models 1 and 2 are obtained in the similar way for the correlation data as described in offline method. It can be seen that under faulty conditions, the magnitude of the projected correlated data will be greater than magnitude of projection under normal conditions. Figure 5.11 and Figure 5.12, shows the residual responses for diode fault. It can be seen that for the case with diode fault, both the residuals exceeds the threshold. Since the diode fault results are also consistent with the FDI logic given in Table 1, and also similar to the result obtained in offline model, It can be inferred that diagnostic model serves an efficient way for detection and isolation of diode faults in the EPGS system.

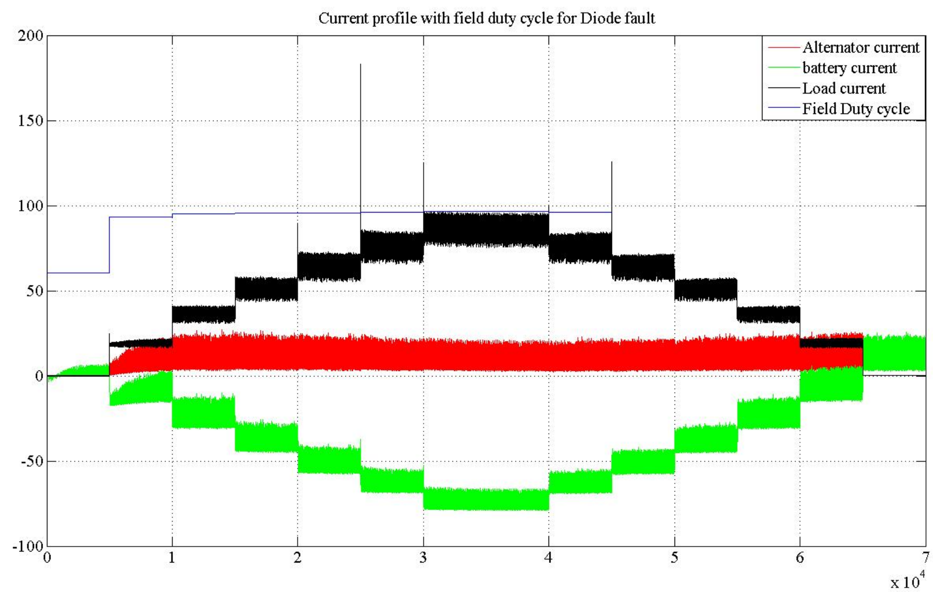

Figure 5.10: Current profile with field duty cycle under Diode short conditions

5.2.3 Regulator fault

As discussed in Chapter 4, the Regulator fault can be determined without making use of principal component model. Hence, it is not considered in the online model.

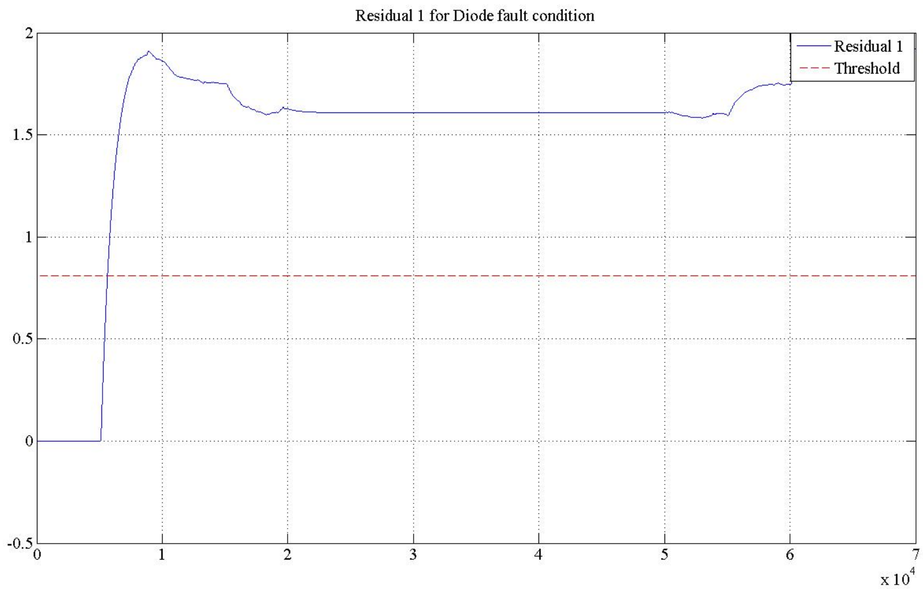

Figure 5.11: Residual 1 under Diode short conditions

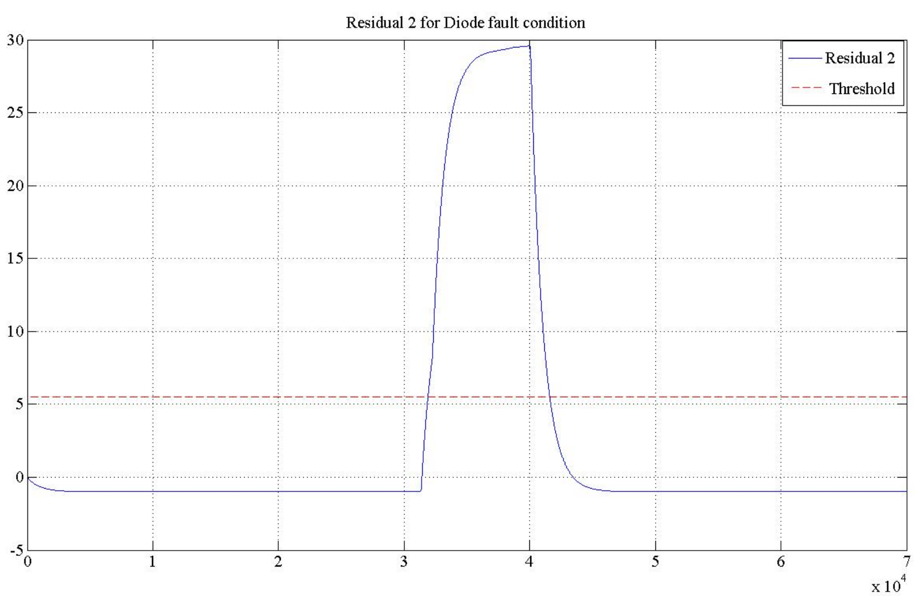

Figure 5.12: Residual 2 under Diode short conditions

Conclusions and Future Work

6.1 Summary

Robust on-board fault diagnostics to ensure the good ”health” of automotive EPGS system are becoming increasing important in modern vehicles. In this thesis, a fault diagnostic method is presented for monitoring alternator related faults in the EPGS systems by utilizing parity relations, which are generated using PCA/MCA techniques. Specifically the contributions of this research work includes the following-

1. Alternator related faults and thier effects were studied.
2. A Matlab/Simulink based EPGS system simulation model was developed and used for algorithm development with the help of General Motors engineers.
3. Fault diagnostic algorithm was developed and the simulation results showed that the fault detection and isolation performance were satisfactory.
4. An IEEE Conference paper written based on this research is being accepted[34].

6.2 Future Work

There are several interesting topics paving path for future research work.

Firstly, in this research the fault diagnostic algorithm was developed and tested mainly on Matlab/Simulink based simulation model. Hence the research results can be further verified to make algorithm evaluation using real bench or vehicle data.

Secondly, the measure of alternator current was assumed to be available in this research. In practise, there is no sensor measuring alternator current in automobiles. Hence further developement of algorithm to estimate alternator current and carry on fault diagnosis would be another interesting work.

Thirdly, the previous research conducted on the EPGS system primarily focussed on battery state of health monitoring algorithms (see, for instance, [31, 33]). And, in this thesis we mainly focussed on fault diagnosis of alternator related faults. Hence, the integration of the presented alternator diagnostics with battery state-of-health monitoring algorithms to achieve system level diagnostics/prognostics would also be another milestone to future work.

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